Alpha and low-beta oscillatory patterns extracted with Canonical Polyadic Decomposition relate to LDA classifier performance in real-life Mobile EEG

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Abstract

The level of attention to cognitive tasks is related to the performance and is therefore likely to also influence the classification accuracy in EEG (auditory) paradigms. Alpha band oscillations (8-12 Hz) in EEG are known to be related to attention and can be quantified through spectral analysis. However, on the channel level, these oscillations are mixed with other brain activity and spatial patterns may vary across tasks. To this end we aim to separate ongoing alpha, theta (4-8 Hz) and low-beta (13-16 Hz) waves in a data driven way and relate it to classifier outcome as obtained by the widely used regularized LDA from a previously recorded outdoor mobile auditory oddball study. The three experimental conditions varied in degree of cognitive load and physical effort. We extract the aforementioned frequency band activity at the single trial level by Canonical Polyadic Decompositon of wavelet-transformed EEG data. Meaningful correlations of the alpha and low-beta-band activity with respect to the subject classification accuracy were found in the two most complex conditions and relate to power band calculations with existing techniques that require electrode selection.

Keywords *Canonical Polyadic Decomposition, Oscillatory patterns, Mobile EEG*

1 Introduction

Recently, mobile EEG has been utilized to investigate attentional paradigms in outdoor conditions (e.g. [1, 2]) Significant differences in task related P300 Event Related Potential (ERP) were identified in real-life ambulatory conditions, as compared to a restricted setup. The influence on the P300 waveform of head and muscle artifacts that arose from being in a fully realistic outdoor biking scenario was found to be minor in previous work [2]. The latter study provided evidence that increased cognitive load in real-life environments is likely to decrease the P300 ERP, which was similar to the thoughts of [1]. Alpha power was found to be diminished in the free biking condition, which may be related to increased attentional demands.

Alpha band activity has been linked to various elements of attentional processing [3]. Low beta components were found to affect attentional processing, as evident through biofeedback training [4]. Theta oscillations were shown to relate to mismatch-negativity responses in MEG data [5]. Being in more demanding scenarios leads to alterations in brain patterns due to automatic (motor) tasks or stronger distractions. For example, significant changes in alpha and beta activation were linked to increasing levels of engagement in virtual reality scenarios [6]. Similar differences might emerge in alpha and beta band characteristics when contrasting real-life recording situations, such as biking outdoors, to more stationary recording environments. Monitoring the alpha and close-by theta and low beta band oscillations on a single-trial basis might reveal additional condition or task-specific effects that are overlooked by the standard analysis which merely focuses on classifier construction and P300 waveform properties [2].

In the current study, we explore the effect of theta (4-8 Hz), alpha (8-12 Hz) and low beta (12-16 Hz) oscillations on classification accuracy as obtained by a widely used regularized Linear Discriminative Analysis (rLDA) classifier. This method was applied to the data from [2], which features three different outdoor mobile recording conditions while the subjects performed a three-class-auditory oddball task. One condition was a completely free ride in an open outdoor environment and can be seen as completely unconstrained.

Canonical Polyadic Decomposition (CPD) is a powerful, data-driven method for extracting ongoing oscillations. CPD was shown to extract relevant alpha sources on a single-trial basis [7]. Decomposing wavelet-transformed EEG data (i.e. Morlet) with CPD, we are able to derive data-driven estimates of the aforementioned oscillations assuming they are present. Each component in the CPD can be characterized by an individual frequency, space and time signature and is classified as theta, alpha and low beta band source if their spectral signature corresponds to the respective frequency bands. In addition, given the nature of CPD, it is possible to remove selected sources. To this end we not only investigate the magnitude of these specific oscillatory components, but also separate them to obtain cleaned EEG datasets.

All in all, we derived meaningful estimates of the amount of alpha and low beta activity which correlate to the classification accuracy at subject level, without the need for selecting appropriate channels.

2 Methods

2.1 Initial Analysis

The data used in the current study is obtained from [2]. To summarize, fifteen subjects (mean age (SD): 27.1 ($\pm$2.5)) participated in the trial and performed a three-class auditory oddball task. The ethics committee of the KU Leuven approved the experimental setup. The acquisition was conducted with a SMARTING mobile EEG amplifier from mBrainTrain (Belgrade, Serbia, www.mbraintrain.com) with 24 Ag/AgCl passive scalp electrodes (Easycap). Extended Infomax ICA was used to remove EOG activity, and then muscle activity was removed through BSS-CCA. All EEG was band-pass filtered ([0.5-20] Hz). After re-referencing offline, the EEG trials consisted of 22 channels and 500 time-points [-200 to 800ms] with zero being the stimulus onset. In addition, data were down-sampled to 40 Hz. Three different outdoor recording conditions with increasing level of cognitive load were measured. One condition involved sitting completely still on a fixed bike (Still). The second condition involved sitting on the fixed bike while pedaling at a comfortable pace (Pedal). The third involved biking freely around the perimeter (Move). During all sessions, the subjects had to attend the target tone and ignore all other tones and (natural) distractions. For the classification procedure, we followed the approach explained in [2]. Classification accuracies were obtained through regularized LDA based on five-fold cross validation. The average rLDA accuracies for the three conditions were: 77.5%, 72.3% and 66.2% for the Still, Pedal and Move conditions, respectively. Two subjects were excluded, as the accuracy was not above chance level for the Move condition (i.e. <55%). Per trial, a continuous wavelet decomposition was applied (i.e. Morlet) with corresponding scales in the 1-16 Hz interval.

2.2 Canonical Polyadic Decomposition

Multidimensional signals can be decomposed by the CPD as a sum of rank-1 terms. For the three-dimensional case, the CPD will decompose a tensor X as follows:

$$X = \sum_{r=1}^{R} a_r \circ b_r \circ c_r + \varepsilon \tag{1}$$

The number of the components is represented by R, the signatures of all atoms in every mode are represented by a_r, b_r, and c_r, and ε represents the error of the model. Every mode has an individual signature which represents the extracted component characterized; in the three-dimensional tensor, which represents the ERP as a structure of channel $\times$ time $\times$ frequency, c_r would provide the frequency signature, b_r the time courses, and a_r would contain the various atoms' spatial distribution. The CPD model operates on a trilinear basis, i.e. the vectors of each mode are proportional to one another within a component of rank-1. In general terms, when the data follows a structure of rank R, unique decomposition occurs up to permutation and scaling of the extracted components. We computed CPD with the NLS (nonlinear least squares) algorithm in Tensorlab toolbox 3.0, which is available publicly. For an overview of the application of tensor models in biomedical signal analysis, we refer the reader to [8].

2.3 Extracting oscillatory components

Low beta 12-16 Hz, alpha 8-12 Hz and theta 4-8 Hz bands were considered in the CPD decomposition and the corresponding CWT scales were used for the decomposition resulting in a 22 channels $\times$ 40 timepoints $\times$ 17 frequency scales tensor. Rank R was set to 3, as this was shown to be adequate in previous work [7]. The models were randomly initialized and repeated several times to investigate significant differences in output. There were no significant differences, which suggests that the CPD extracted components are stable.

To quantify and select appropriate oscillatory components, we detected the peak in each component's spectral mode and categorized it as theta, alpha or low beta if the index was in one of the corresponding frequency bands. With R=3 CPD will extract 3 components which together explain the most possible variance of the signal. Therefore, if the brain oscillation of interest have low power, it is possible that one or more of the frequency bands of interest are not represented in the components. Figure 1a illustrates a derived single-trial component of subject 1, and the spatial, temporal and spectral modes are depicted from top to bottom, respectively. The source was categorized as an alpha band source, as is evident from the spectral mode. This process was repeated for all trials to obtain, per subject and condition, a number of trials that were categorized into at least one of the three frequency bands. This was in turn correlated to the subject average accuracies as obtained with rLDA.

2.4 Removing selected components

Besides detection, we also reconstruct the frequency band-specific information from the CPD component by multiplying the temporal and spectral mode and scaling it by the channel weight in the decomposition. This process generates per channel a matrix that estimates the source's contribution for a given trial. The result was subtracted from the original wavelet transformed data and an inverse wavelet transform was applied consecutively to obtain cleaned channel $\times$ time data in which the selected component is removed. An example of removing the alpha source from Fig. 1A has been illustrated in Fig. 1B.

2.5 Validation

To validate the data-driven CPD estimates, the frequency estimation process was repeated manually by calculating the normalized band power (based on power spectral density) on three different spatial locations to

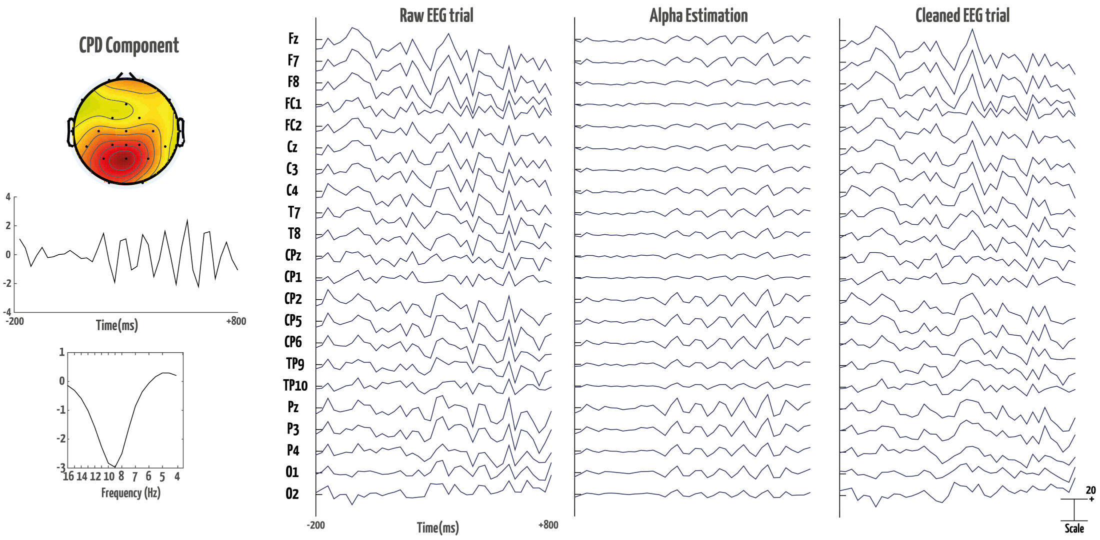

Figure 1: A) A single alpha component of the CPD model of subject 1. From top to bottom, the spatial, temporal and spectral modes are depicted. B) Example of the single-trial EEG data from (a) and the reconstructed alpha patterns by back-reconstructing the CPD component and applying an inverse wavelet transform on the filtered time-frequency matrix provides the cleaned EEG trial.

capture frontal, central and posterior oscillations at channels Fz, Cz and O1 respectively. Removal of these oscillations was achieved by applying a stop-band FIR filter on the selected frequency band on all channels. This will be referred to as the reference method.

3 Results

3.1 Subject-level

A theta band component was detected in nearly all trials: 93.9% in the Still condition, 94.0% in the Pedal condition, and 94.2% in the Move condition. For the alpha band, 74.0%, 72.2% and 70% of the trials were identified to have at least one alpha band component for the Still, Pedal and Move conditions, respectively. Compared to the Pedal (8.7%) and Still (8.5%) conditions we saw an increase in low-beta band quantity in the Move condition, 13.5%. Correlating the subject-average number of alpha trials to the classification accuracy revealed a marginally significant negative correlation (r= -0.51, p = 0.07) in the Pedal condition. Similarly, the low-beta activity correlated marginally with the Pedal condition accuracies as well (r= -0.51, p = 0.08). In addition, a significant correlation was found between the low-beta and rLDA accuracies in the Move condition (r= -0.65, p <0.05). These correlations and median spatial plots of the CPD extracted components are illustrated in figure 2. The theta band did not correlate (p >0.1) with the rLDA accuracies in any condition. For this reason, results of the theta band and still condition are omitted in the figures, for brevity. Interestingly, no significant correlations between the reference power band estimations on the posterior channel with either band were found. The frontal and central channel estimation of low-beta in the Move condition as extracted by the reference method correlated in similar fashion to the rLDA accuracy as the CPD results (r= -0.72, p <0.05) and (r= -0.74, p <0.01) respectively. Significant correlation of the reference power bands and the Pedal condition were absent, only similar (negative) trends can be noted.

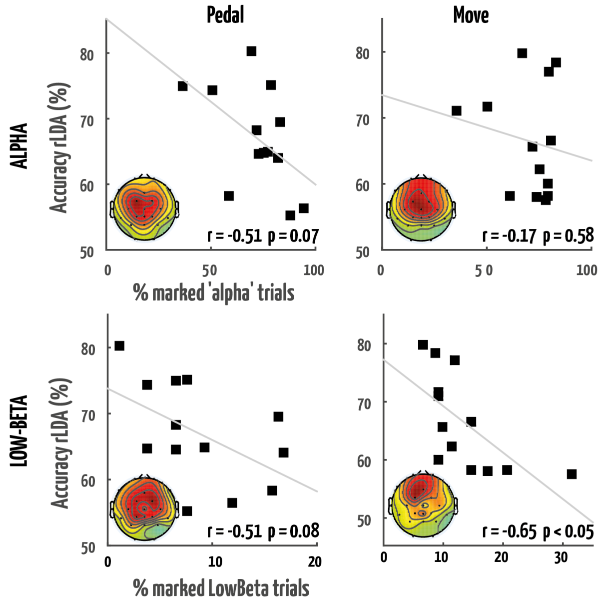

Figure 2: Scatterplots and correlations between the number of trials noted as alpha (top) or low-beta (bottom) by the CPD and the average accuracy. Each data point represents a single subject. The lines are best fit (Least-squares) to the data points and are for illustrative purposes only. The topoplots represent the median spatial mode of the extracted components.

3.2 Removal at Single-Trial level

Finally, we removed the selected oscillatory CPD components per trial from the alpha and low-beta band as these correlated with the average rLDA accuracy. Table 1 represents the grand average classification accuracies for the reference rLDA and for the removal of alpha or low-beta activity on the indicated trials. The accuracy in the move condition improved significantly after removal of the alpha activity (t_{12}=2.65, p <0.05). This increase in accuracy was evident for 10 of the 13 subjects. In the other conditions no significant changes can be noted. Applying the reference stopband filter on the alpha and low-beta bands resulted in similar effects on the classification accuracy as the CPD correction; in the Move condition a slightly higher accuracy was evident (t_{12}=2.21,p <0.05).

Table 1: Average classification accuracies in the Still, Pedal and Move conditions for the regular data (Reference), with removal of alpha activity and low-beta as extracted by the CPD. Significant differences (p <0.05) with respect to the reference are indicated with an asterix.

	Still	Pedal	Move
Initial Accuracy	77.5%	72.3%	66.2%
Alpha Removal	76.9%	72.7%	68.3% *
Low-beta Removal	77.0%	72.4%	66.3%

4 Conclusion and Discussion

We identified meaningful correlations with respect to single-subject performance on the auditory oddball task in the alpha and low-beta band for the Pedal and Move conditions. The extracted theta band activity did not correlate with the classifier performance. Similar results were obtained with existing band power estimation techniques, although the latter requires appropriate selection of spatial location and was less predictive of user rLDA performance in the Pedal condition. This illustrates that the frequency components that were extracted in a data driven way by CPD were meaningful and can be applied in an automated fashion. In addition, removal of the extracted alpha oscillatory activity increased the grand average accuracy in the Move condition. Finally, in all conditions we illustrated that we did not remove discriminative information related to the task.

CPD estimates components' spatial, temporal and spectral characteristics based on the patterns in the data tensor. This way, relevant electrodes that convey similar spectral activity are clustered in a single component. Calculating frequency power on the original [channel $\times$ time $\times$ frequency] tensor requires selection of (a) specific channel(s). For example, posterior channels did not seem to capture predictive alpha and low-beta oscillations whereas the more central and frontal CPD extracted patterns did (Fig. 2). Correcting for the alpha activity increased the classification accuracy in the Move condition. This indicates that the alpha activity, or at least part of it, had a negative effect on the task-related ERP signal. This is a surprising finding, as the alpha power was shown to be low in the Move condition compared to the others [2].

Deriving spectral features that correlate with classifier performance might be a promising addition for evaluating subject differences or tuning classifier characteristics. On a single-trial level, similar derivations have been made in phase-locking value which has been reported to provide valuable information of stimulus-locked oscillations that in turn influence the ERPs of interest [9, 10].

Finally, an extension of the CPD model to a Block Term Decomposition (BTD) might allow for better extraction of the spatio-spectral signatures in our model [11]. A BTD can allow two or more modes to be of higher rank, allowing more variation to be modeled. In the current framework, BTD might be able to capture shifts in phase of the various oscillations over electrodes.

To conclude, the presented work provides exploratory results on the effect of theta, alpha and low-beta oscillations on the classifier performance, contrasting the results between three different outdoor mobile-recorded datasets. Especially in unconstrained or physically engaging scenarios, evaluating these patterns in a data-driven way can provide valuable information on predicted classifier performance.

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